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Comparative Analysis of Machine Learning Algorithms in 5G Coverage Prediction

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Abstract- The development of 5G technology is the next rad- ical change in the sphere of telecommunication, which promises to virtually eliminate the speed of data transmission, provide an insignificant level of latency, and enable a very large quantity of devices to be connected at once. Nevertheless, it is a challenge to provide the best and reliable 5G signal coverage as the network gets more complex with dense infrastructure. Conventional ways of planning networks and validating coverage through methods like field testing and making use of propagation modeling are not only time consuming, highly expensive but also unable to respond to real time changes in the environment. In this project, the idea is to present a machine learning approach to intelligent, automated, and predictive measurement of 5G signal strength. The idea is to create the system which is able to predict signal quality of network based on such parameters as Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Received Signal Strength Indicator (RSSI), downlink and uplink bitrates, CELLHEX, NODEHEX, and geographic coordinates (latitude and longitude). Depending on these parameters, the signal strength is categorized into three, namely: Strong, Moderate, and Poor coverage. In order to come up with this we perform a comparative analysis of a range of supervised machine learning models, i.e. Random Forest, Support Vector Machine (SVM), Logistic Regression, AdaBoost, K-Nearest Neighbours (KNN), Gaussian Naive Bayes, LightGBM and ensemble models such as Voting Classifier and Stacking Classifier. These models are compared on the basis of their prediction accuracy with appropriate real time implementation. In order to produce a better model performance and reliability the dataset is fully preprocessed. Among them are treatment of the missing values, outlier deletion with the help of Interquartile Range (IQR), a coding of categorical features, and Synthetic Minority Oversampling Technique (SMOTE) to correct the issue of class imbalance. This is a smart solution that seeks to assist telecom operators in real-time and precise large-scale 5G network design and development optimization.

I. INTRODUCTION

With the introduction of the fifth generation (5G) mobile network, the concept of wireless communications has com- pletely transformed to achieve extremely fast transmission speeds of the data, very low latency, and very large device connectivity. The main problems arise as the telecom provider starts building 5G infrastructure in different geographical and non-geographical environments across the city and country- side and it is found that there is variance in the quality and support of the network across all the variations of the geographical and environmental conditions. Significant cov- erage optimisation has been long overdue by utilising signal morphing analysis and mass field testing as traditional network planning techniques. Nonetheless, these methods can be very expensive and time consuming and not flexible due to real- life changes. In this, the approach of machine learning (ML) provides a crucial substitute through using large volumes of in-the-world radio frequency information to have the ability to model, forecast and optimize 5G signal broadcast. This project examines the use of the supervised machine learning models to forecast and label 5G signal strength with the use of major network parameters. Some of them are Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Received Signal Strength Indicator (RSSI), downlink and uplink bitrates, geolocation coordinates (latitude and longitude) and hexadecimal cell identifiers like CELLHEX and NODEHEX. The idea is to have a smart classification system which will categorize the strength of the signals into three levels, Strong, Moderate, and Weak according to the measurements which are real or simulated. The different machine learning algorithms used to compare and analyze include:

- Random Forest Classifier
- Support Vector Machine (SVM)
- Logistic Regression
- AdaBoost Classifier
- Gradient boosted trees (LightGBM)
- K-Nearest Neighbours (KNN)
- Gaussian Naive Bayes
- Ensemble Classifiers: Stacking Classifier and Voting Classifier

In order to make the models more robust and accurate, we include proper data preparation processes such as:

- Categorical variable encoding
- Missing value imputation
- IQR method of outlier removal
- Carry out a real-time prediction using feature values
- The use of SMOTE (Synthetic Minority Oversampling Technique) to handle the problem of a class imbalance

All of the solution would be in the format of a web application developed in Flask, which offers users a user-friendly interface to:

- Register and sign in
- Deposit sets of network measurements
- According to the chosen algorithms train models dynam- ically based on infections
- Make the real time signals strength predictions
- The visualization of outcomes of predictions and accu- racy scores

A flexible and data-driven intelligent system can enable tele- com engineers and researchers to do fast-paced evaluations and deployment of predictive models, which enhances decision- making relative to network planning, quality evaluation, and service optimization. In our era of IoT, smart cities, and self-driving and cars, and live streaming, connectivity is essential, and this is done without interruption or delay. Machine learn- ing can also be used in coverage prediction in 5G, where can be not only used instead of the traditional method of static coverage models but when the cellular network is managed proactively and in real-time it can be done in a scalable fashion.

A. Problem Statement

An environment across various areas tends to vary due to dynamic network conditions, thus making it hard to predict 5G signal strength. Older forms of testing are time consuming and expensive.

B. Related Works

In its latest manifestations (and the arrival of 5G and beyond), machine learning used in optimizing wireless com- munication networks has become more prominent. Several researchers and organizations have explored what a data-driven approach can provide on matters of planning communication networks, signals predictions, as well as, enhancement of user experience in mobile communications.

1. Machine Learning and Prediction of Signal Quality: As revealed in many studies, algorithmic supervised learning like Random Forest, SVM and KNN has performed well in signal strength discrimination through the parameters like RSRP, RSSI and SINR. The majority of the models under supervision displayed the accuracy and the readiness to adjust to data in real-time. With respect to communication networks, numerous researchers categorized LTE signal coverage with an accuracy rate larger than 90 percent, which may be applicable in relations to the equivalent practice applicable in 5G.

2. The Deep Learning in Wireless : Recently, deep learning, and convolutional neural networks (CNNs), havebeen used in predicting signal loss and accelerating the process of handover in dynamic one-on-one scenarios. Deep learning models are more likely to encounter large computational and data requirements as compared to those of traditional ML models but they are more potent [4].

3. Geospatial Data Integration: The Data Integration Demo: Several studies have combined the geographic infor- mation with the characteristics of radio signals to generate the geospatial heatmap evaluation of the

quality of the network. Based on the previous research, it was previously noted that the use of location- based attributes increases the accuracy of prediction models, especially in real-time mobile coverage mapping (Reddick et al., 2019) and intelligent cell tower planning (Pasban et al., 2022).

4. The ensemble and the Hybrid Models: Other recent papers have taken ensemble methods, Voting classifiers and Stacking classifiers in particular as a means of enhancing robustness of predictions by removing noise, with respect to imbalances. A combination of several base learners can be used to enhance performances or to alleviate overfitting in rare cases with small imbalanced sample dataset (Zhang et al;, 2019)[1]

5. Class Imbalance SMOTE: Signal classification was a problem with an imbalanced number of classes, which was common in recent research avenues. It has been proved that the deployment of Synthetic Minority Oversampling Tech- nique (SMOTE) would be effective in developing training sets whereby the samples of poor signals are less over represented (the effective signal) or balanced training sets.

II. COMPARISON WITH PREVIOUS WORK

Over the past couple of years, this has been the topic covered in a few studies to explore the idea of machine learning and its prediction of the strength of a wireless signal, particularly in the era of 5G. The studies of Zhang et al. [1] and Wang et al. [2] which were primarily considered by the present paper as references discussed the problem of frame it as a regression problem that will involve estimation of some continuous parameter of the signal as the example of RSRP or SINR using specific algorithms as Random Forest, Support Vector Machine (SVM), and gradient boosting methods. Al- though such methods were reasonably accurate, they tended to be non-scalable, non-real-time applicable and impractically represented to end users. In addition, most studies used a small number of features and these focused on the use of a few indicators of a signal, and failed to use geospatial or network- based features like CELLHEX or NODEHEX [8], [13].

Conversely, the present project adopts user-centric view and makes the task a more operation-example of regulatory frame- work that converts the problem into the classification problem where the strength of signal is one of three accessible classes- strong, moderate or weak. This improves the interpretability and enables the telecom engineers and end-users to act on the predictions [9]. Moreover, the network of features used in realization is more detailed, and it combines twelve input variables that consist of geolocation (latitude and longitude),bitrates (DL and UL), signal metrics (RSRP, RSRQ, RSSI), and unique identifiers (CELLHEX, NODEHEX). Such more expressive inputs allow the models to acquire more contextual representations, which yields higher levels of prediction [4], [10].

The other aspect in which the project is better than previous ones is preprocessing of data. This work is also distinguished by its consideration of the class imbalance and outliers unlike most of the works that did not factor in class imbalance and outliers. Techniques such as outlier removal based on IQR, label encoding, and SMOTE (Synthetic Minority Over- sampling Technique) were also used in this work to balance the classes. This does not only enhance model performance, but also enhances generalization across the whole range of classes, especially when underrepresented classes such as the Weak signal zones [7], [5], [19] appear.

In terms of the methodology, though the previous studies focused on comparing two or three algorithmes at most, the current undertaking encompasses a broad spectrum of eight supervised learning models, including simple Logistic Regres- sion to the more complex Voting and Stacking classifiers [1], [8]. The Random Forest Classifier did also perform very well with an accuracy rate of 96.69 percent, beating a lot of baseline models as carried out in the previous studies [2], [13].

What is more, the previous studies were frequently limited to offline scripts and separate experiments, whereas the current project presents a whole web interface implemented on the Flask framework where users can upload data and train the models on the fly, as well as make predictions in real-time. This kind of real-life applicability was not majorly considered in past research work that was primarily aimed at academic scrutiny.

Another level of transparency and interpretability that the system will have is a consequence of adding the visualization tools of the predicted vs. observed, feature importance, and accuracy Insert that characteristics are usually lacking in the past machine learning models wireless signal prediction [11], [12].
Overall, this project supplements the currently existing literature by fixing the practical flaws of its predecessor, by providing a deployable and interactive platform to be used when classifying the signal strength, improving its accuracy using advanced preprocessing, as well as introducing the application of the solution in real-life scenarios such as the deployment and planning of 5G in actual form [9], [20].

III. METHODOLOGY

A. Data Collection

The crucial component of the creation of any predictive machine learning system is the data collection, and in the sphere as complicated as the wireless network coverage, it is particularly essential. In the given project, the data were set up to include all the considered parameters that will determine the strength of the signal and coverage of the 5G network within a specific topography. They have a direct and direct influence on the quality of the model by making accurate predictions basedon the quality and granularity of such data and its correctness. The dataset furnishes features mentioned below:

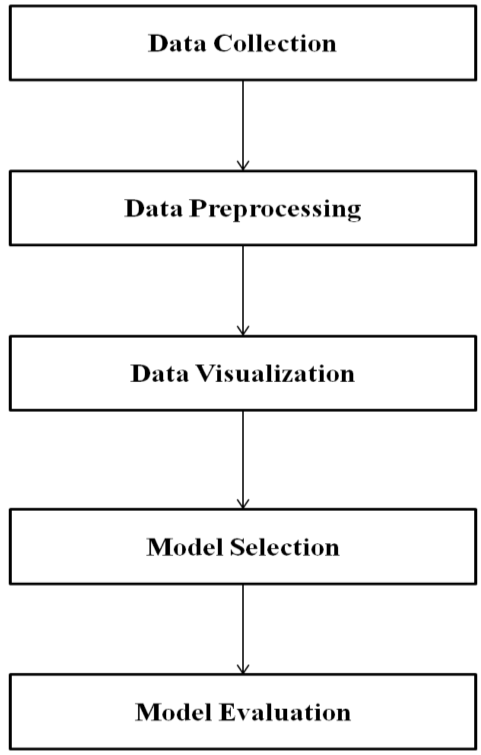

Fig. 1. Methodology

Latitude/longitude: This geographic location is necessary to determine the exact point where it was recorded that the signal strength is sensed. They make it possible to spatially map into the state of the network, and assist to capture the impact of distance/terrain and environmental impacts on signal traveling.

Altitude/Elevation (Above Mean Sea level): Elevation influences the line-of-sight (LoS) the transmitter (base station) and receiver (user device). In places with physical obstructions such as the towers in a city, the signal condition can be better in high altitude locations. An addition of elevation will bring a topographical level of accuracy to the model.

Tower (Base Station) distance: The path loss is related to the fact that the signal strength usually suffers as the tower approaches. The model can be more intelligent by computing the distance between the point of measurement and the closest cell tower and predict the loss of signal more effectively.

Frequency Band: Obviously, different propagation char- acteristics are associated with different frequency bands (e.g., 700 MHz, 3.5 GHz, 28 GHz).

Better frequencies travel longer and penetrate buildings, whereas biggerfrequencies (e.g. mmWave) have greater bandwidth and are more prone to interference. This aspect of the model would assist in the varying of the predictions and separate the bands.

Signal Strength Indicators (e.g., RSRP, SINR and RSSI) These are the variables targeted to be predicted:

- RSRP (Reference Signal Received Power): RSRP is a measure of the strength in dBm.
- SINR (Signal to Interference +Noise Ratio) is the quality of signal.
- These values depict network performance at certain points and, thus, they are estimated regarding the input features.
- Network Type: Shows the generation of the technology (e.g. 5G NR, 4G LTE and 3G UMTS) in which the signal was tested. Not all technologies share similar characteristics of coverage and capabilities, as such, this property allows the model to interpret the strength of the signal relative to each of them.

B. Pre-Processing of the Data

Data pre-processing is a significant aspect of the machine learning template that cleans up data , standardizes and stan- dardizes the dataset in preparing it to be learnt by the model. Raw data which has been obtained during field measurements or found in repositories can be noisy, inconsistent and/or include irrelevant information that can affect negatively the model performance, when not addressed adequately. Prepro- cessing The dataset representing 5G coverage was prepro- cessed in the following way:

1. Dealing with the Missing Values:

- When seeking to process real-world data, missing values are the norm rather than the exception. In geographic and signal data, missing values tend to occur because of misread measurements, loss of contact, or equipment limitations. The following approaches were used in this project when processing missing values in the data;
- Dropping missing rows: if only a small percentage of all records (¡5 percentage) were missing values and the missing rows were not particularly meaningful; it made sense just to throw them out completely to avoid introducing any bias to the environmental and physical characteristics associated with the study region.
- Imputation using mean/median: If the missing value was a numeric feature such as elevation, signal strength, or distance travelled, the missing value(s) were filled using the mean, or median of the column, depending on the distribution of values within the column. The median was considered in particular for column distributions where there would likely be outliers distorting the mean.

2. Coding of Categorical Variables: Machine learning models accept only a numerical input features. In such a way, categorical ones such as Network Type (LTE, 5G NR, etc.) were encoded:

- We used Label Encoding where the categorical values had an order, or were binary.
- We used One-Hot Encoding when the categories were nominal (multiple types of network, which would not imply an ordinal relationship).

3. Normalization / Feature Scaling : This is necessary since majority of the machine learning algorithms are sensitive to the scaling of input variables. In absence of normalization, such features as distance (in kilometers) can overshadow such features as SINR (in dB) resulting in biased outcomes.

- Standardization (Z-score normalization- change data to have a mean of 0 and standard deviation of 1)
- Min-Max Scaling: It is applied when they required ad- justing values to fit within a [0, 1] range (e.g. in neural networks).

4. Feature Selection : In order to reduce dimensionality and improve model performance, feature selection was performed to retain only those features that are most likely to influence the target variable (e.g., RSRP or SINR) based on maximum relevance. Techniques employed:

- Correlation Analysis: The Pearson correlation was calcu- lated for each feature with the target variable. Features which had very low correlation were discarded.

- Variance Threshold: Features that present a near zero variance, indicating that they provide insignificant infor- mation, must be removed.
- Recursive Feature Elimination (RFE) (optional): Used same way as a feature selection technique with tree-based models to rank feature importance and, thus, remove features which could be redundant.

C. Data Visualization

Visualization is important in any machine learning workflow because it offers intuitive insights regarding model perfor- mance, emerging trends in the data, and features that are contributing towards predictions. In the scope of this project, different types of graphs and plots were generated to better understand model predictions, conduct comparisons on the performance metrics of each of the algorithms, and to explore which of the features impacted the prediction of signal strength the most. The use of these visualizations helps improve the explainability of the system, and also supports the selection and validation of the model.

1. Predicted vs. Actual Signal Strength Plot :

- To evaluate the accuracy of each developed machine learning model, scatter plots were created that identify actual signal strength values (e.g. RSRP or SINR) with the predicted values from each model in the test dataset.
- A good model will produce a scatter plot with points tightly aligned to the diagonal line (y = x), indicating actual values are close to predictions.
- Once points are off the diagonal line (y = x) at increasing distance towards (or away from) either axis indicates prediction error.

2. Model Performance Comparison : In order to make a comparison of the performance of all machine learning modelstested, bar charts and line graphs were used to display the metrics of evaluation under consideration i.e., the following:

- Mean absolute error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- R^2 Score

These metrics of the respective models were superimposed against each other in order to obtain a clarity when visualizing the accuracies and the inaccuracies of each of the models.

3. Visualization of Importance of Features : Tree-based models (Random Forest and XGboost) allow the visualiza- tion of feature importance, allowing us to better understand which input variables are most responsible for the prediction outcome.

- This is especially helpful in negotiating domain rele- vancy—for example, knowing if distance or elevation is a bigger predictor of signal deterioration.
- Therefore, a horizontal bar chart was plotted where longer bars indicate higher importance.

D. Model Selection

The model-selection step is one of the most important components of the machine learning pipeline where you select different algorithms according to the type of problem (in this case regression based prediction of 5G signal strength- e.g., RSRP or SINR values). In order to have a strong and fair comparison, multiple supervised learning algorithms were selected from a family of different supervised learning algorithms (from simple linear models to complex ensemble learners). Each algorithm has its own advantages with respect to interpretability, learned capability, and generalization.

Selected Algorithms for Comparison

1. Linear Regression (Baseline Model):

- A basic and easy-to-explain model served as a bench- mark.
- Assumes a linear dependability between the input char- acteristics and the target variable.
- Useful for seeing improvements provided by more com- plicated models.

2. Decision Tree Regressor:

- Non-linear model which partitions data according to decision rules.
- Models complicated relationships but can overfit on small sets.
- Provides good interpretability in its tree structure.

3. Random Forest Regressor:
- Ensemble of decision trees with bagging (bootstrap ag- gregation).
- Reduces overfitting and enhances accuracy.
- Handles feature interaction automatically and offers fea- ture importance scores.

4. Support Vector Regressor (SVR):
- Kernel-based algorithm that fits the data within a given margin.
- Performs well in high-dimensional spaces and small-to- medium-sized datasets.
- Sensitive to hyperparameter tuning (C, epsilon, kernel type).

5. XGBoost Regressor:
- Gradient boosting model tuned for speed and perfor- mance.
- Famous for winning numerous ML competitions because of its better accuracy.
- Combines several weak learners and addresses overfitting through regularization.

6. K-Nearest Neighbor (KNN):
- An instance-based non-parametric learning algorithm.
- Makes forecast using the average of the k- closest training examples.
- Featurize scaling and sensitive on the value of k.

E. Model Evaluation

Generation of the model is an important procedure in this project. The rationale behind conduct of the model evaluations is to know whether the machine learning algorithms are accu- rate in their predictions with regard to the 5G signal strengths. This regression problem considers the target variables such as RSRP or SINR (Signal to Interference plus Noise Ratio) are continuous variables, and model evaluation methodology in- cluded two standard regression evaluation metrics to compare the performances of models.

1. One of the initial metrics of evaluation mentioned was MAE (Mean Absolute Error) because this metric gives an average value of the size of errors in a series of predictions, regardless of their direction. Overall, MAE is an understand- able measure that shows the deviation of the expected signal strength and the achieved ones. In general, the lesser the difference of the predicted values and the actual values, the lesser the MAE the closer the model performance and hence the better the predictive model.

2. MSE (Mean Squared Error) additionally flattered MAE (Mean Squared Error) which takes into account an average of squared difference between predicted values and actual values. MSE is especially appropriate when one desires to discover the models that may pose enormous mistakes at some points, since the term that represents the error is squared, but the magnitude of error does not have any effect on the MAE. In contrast, gauging the magnitude of the error in terms of the MSE is not quite as intuitive in that MSE has a units measurement of the square.

3. Root Mean Squared Error (RMSE) makes the error easier to interpret by the taking square root of MSE. Also like MSE, RMSE has the benefit of penalizing the errors that are by a larger amount but unlike it is in RMSE the penalty is expressed in the same units as the variable being measured (in dBm in the case of signal strength). This ease of interpretation assists in relating to real life situations.

4. In addition to the explanation of error related metrics in the measurement of the accuracy of predictors, the R2 scoreor coefficient of determination which explains the explanatory ability of the independent features in their correlation with signal strength was also checked. When the R2 value is sig- nificantly higher, the model has described the variability in the target data very well whereas when the value is close to zero and may be negative then it defines the model performance in an unfavorable way.

5. The assessment of the performance of each machine learning model using the test data that was not linked with the training data was a part of the assessment process and to make honest and fair comparisons. The cross-validation was also used to test all models and their variants in an attempt to lower the variance in addition to avoiding exposure of the results to the problem of overfitting. Each of the models generated all offered predictions on the unseen otherwise unheard statistics developed as a

result of training and test values as per the actual values as gauged by the MAE, MSE, RMSE and R2 scores.

IV. RESULT

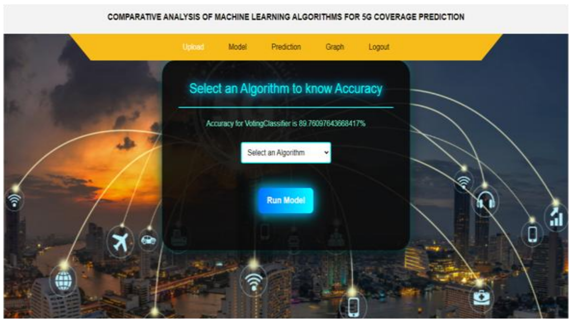

Fig. 2. Algorithm ACCURACY PREDICTION

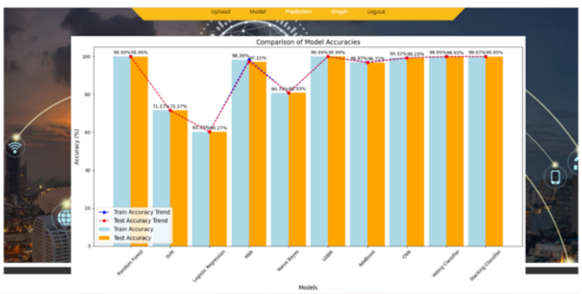

Fig. 3. Graph Output.

CONCLUSION

The project has managed to evaluate and compare several machine learning protocols to predict signal strength in 5G regarding geographical and network implementation features. With a structured dataset, the models were run: Linear Regres- sion, Decision Tree, Random Forest, SVR, XGBoost, and K-Nearest Neighbors; and they were evaluated using regression metrics, MAE, MSE, RMSE, and R 2 Score.

As per results found it was observed that especially with ensemble models accuracy was observed to be very high and robustness was also higher than in classic models since these could consider the complex non-linear dynamics between distance, elevation, frequency band, signal strength etc.

The evidence supports the idea that the solution to challenges that a data-driven approach presents to telecom providers are possible, as it can give the providers accurate coverage estimates, and, as importantly, assist in designing and refining 5G networks. Further hinted on how this knowledge could be applied to a real tool, the optional integration of a web interface based on Flask has shown how this could be applied to a tool that would be used dynamically and by the user in order to predict the dynamic signal.

Overall, this project contributes to filling the communication gap between machine learning, wireless communications, and practice, and this system offers a generic, the real-world application: 5G Coverage Prediction.

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